Received: 24 November 2017 | Revised: 29 May 2019 | Accepted: 11 June 2019 | Published on: 16 July 2019

DOI: 10.1002/met.1817

RESEARCH ARTICLE

Meteorological Applications RMetS

Novel approaches for air temperature prediction: A comparison of four hybrid evolutionary fuzzy models

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Abstract

The application of a novel method of adaptive neuro-fuzzy inference system (ANFIS) for the prediction of air temperature is investigated. The paper discusses the improvement of the ANFIS when used with genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization for continuous domains (ACO_R) and differential evolution (DE). For this purpose, three input of multiple variables are selected in order to predict monthly minimum, average and maximum air temperatures for 34 meteorological stations in Iran. The co-efficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and Nash–Sutcliffe efficiency (NSE) are used as evaluation criteria. A comparison of suggested fuzzy models indicates that the ANFIS with the GA has the best performance in the prediction of maximum temperatures. It decreases the RMSE of the classic ANFIS model in the validation stage from 1.22 to 1.12°C for Mashhad, from 1.26 to 1.01°C for Zahedan, from 1.20 to 0.98°C for Ahvaz, from 1.76 to 1.24°C for Rasht and from 1.21 to 0.95°C for Tabriz.

KEYWORDS

adaptive neuro-fuzzy inference system (ANFIS), evolutionary algorithm (EA), extreme and average temperature, genetic algorithm (GA)

1 | INTRODUCTION

Air temperature is of fundamental importance in irrigation, hydrology, agriculture and ecology (Benavides *et al.*, 2007). Accurate predictions of temperature are needed for planning agricultural operation, travel and recreational activities, energy generation as well as developing measures to cope with temperature fluctuations (George, 2001).

In recent years, many studies in different fields using soft computing models such as artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS) and gene expression programming (GEP) have been used for the estimation and prediction of different parameters associated with dynamical nonlinear processes (Ustaoglu *et al.*, 2008; Abhishek *et al.*, 2012; Shiri *et al.*, 2014a; 2014b; Kiafar *et al.*, 2017; Landeras *et al.*, 2017; Shiri, 2017).

These studies showed that ANFIS is one of the best models for the prediction of various phenomena. The ANFIS, proposed by Jang (1993), is a multilayer feed-forward network that uses learning algorithms as well as fuzzy rules for operating desired functions. It is attractive, since it can learn the underlying relations of numerical data, while the fuzzy rules can provide a transparent linguistic description of the model works. Fuzzy systems provide the possibility of integrating (logical) information processing with the attractive mathematical properties of general function approximators (Setnes *et al*., 1998). Various studies have already considered engineering applications of neural-fuzzy modelling in hydrogeological and environmental-based systems (Gavili *et al*., 2017; Yavari *et al*., 2017).

In neural or neuro-fuzzy networks, determining the suitable structure of the network and the selection of parameters have considerable importance. The success of these models is dependent on the accuracy and efficiency of their training algorithms. Gradient algorithms, especially back propagation, and Levenberg–Marquardt, are considered the most usable among all the variable training algorithms for neural networks. Despite these algorithms being widely used in many applications, users need to be aware of their weaknesses. For example, algorithms based on a local minimum (or maximum) of a function using a gradient descent (ascend) are prone to discover solely local optimal points (Azad *et al*., 2018a). Moreover, some of these training algorithms, such as Levenberg–Marquardt, are computationally complex and require high computational memory for calculations that cannot be optimized. Therefore, new methods are required that do not have the shortcomings of gradient-based algorithms. The evolutionary algorithm (EA) has the ability to search globally without providing exclusively local optimal points. Moreover, if an appropriate algorithm is used, a complex problem with high computational volume can be easily optimized.

JalalKamali (2015) used the ANFIS optimized with the GA and PSO (ANFIS-GA and ANFIS-PSO) in order to predict groundwater quality of Kerman province, located in the centre of Iran. The ANFIS-PSO was also used by Basser *et al*. (2015) to estimate the optimal parameters of a protective spur dike. Tabari (2016) integrated a fuzzy inference system and direct search optimization algorithm (FIS-DSOA) to forecast daily runoff in the downstream reach of the Taleghan River in Iran. Kisi *et al*. (2017a, 2017b) optimized the ANN performance for groundwater fluctuation forecasts using the GA, PSO and imperialist competitive algorithm (ICA). Azad *et al*. (2018a) reported that the differential evolution (DE) algorithm improved the ANFIS performance when estimating river water-quality parameters. Kisi *et al*. (2017a, 2017b) reported that the PSO and DE algorithms improved the ability of the ANFIS to predict groundwater quality parameters.

A literature survey shows that, in most cases, the ANFIS is appropriate for hydrological and environmental phenomena, but its performance needs to be improved. The impact of evolutionary training algorithms on the improvement of the ANFIS has not been assessed previously. The objective of the present study is as follows:

- To present comprehensive inputs to forecast air temperature in different climatic conditions.
- To explore the possibility of improving ANFIS performance in air temperature prediction by using evolutionary training algorithms.
- To evaluate the ability of the genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization for continuous domains (ACO_R) and DE to improve the ANFIS when forecasting minimum, mean and maximum air temperatures.

2 | MATERIALS AND METHODS

2.1 | Adaptive neuro-fuzzy inference system (ANFIS)

The present study used three methods: grid partition (GP), subtractive clustering (SC) and fuzzy c-means clustering (FCM) to generate a basic FIS. Initial results showed that the FCM was better than the SC and GP (Kisi *et al*., 2018). Therefore, it was used to train a simple ANFIS with the inclusion of a back-propagation and hybrid training algorithm. The use of the back-propagation algorithm provided more predictions. The better performance of the back-propagation method can be based on its better ability in comparison with a hybrid in order to adapt with data when it turns from the train section to the test section. It is notable that some other studies support these results (Kisi and Sanikhani, 2015; Azad *et al*., 2018b). Moreover, sensitivity studies showed that 500 iterations were sufficient to achieve improved model performance, and more iterations had no impact on the final results (Sanikhani *et al*., 2015). A total of 360 available data (monthly temperature) were divided into train (60%), validation (20%) and test (20%) stages. Matlab r (2014) software was used in the ANFIS analyses.

2.2 | Application of evolutionary algorithms (EA) to optimize ANFIS performance

2.2.1 | Continuous genetic algorithm (CGA) and ant colony optimization (ACO) for a continuous domain

The GA and ACO are algorithms widely used in optimization problems and have been used in many applications. The GA is an optimization method based on the evolution of living beings, and it follows evolution process rules (Holland, 1975). The ACO optimizes problems using the food search method of ants (Bilchev and Parmee, 1995). The two methods perform better when solving discrete problems, while the problem of interest in the current paper is of continuous nature. Therefore, the CGA and ACO_R (Socha and Dorigo, 2008; Arqub and Abo-Hammour, 2014) are better suited for

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the present application. They have moderate convergence speed and a better performance in the optimization of complicated phenomena or large computational tasks. Such algorithms adopt global optimum point searches and are suitable for continuous problems (Kisi *et al*., 2017a, 2017b).

The modelling steps of air temperature using the optimized ANFIS by the CGA and ACO_R are shown in Figure 1. The structure of the proposed models is summarized below.

Input and output data are uploaded based on a predetermined classification for three stages, including training, validation and test (Figure 1a). A fuzzy system is created by one of the FCM, GP and SC methods (Figure 1b). Note that the results obtained by primary modelling here showed that the FCM method had the best performance (Mirrashid, 2014; Abdulshahed *et al*., 2015; Rajabi *et al*., 2017; Azad *et al*., 2018b). Therefore, the FCM was used to generate the fuzzy system in all hybrid models (ANFIS models with EA). The model is trained using the proposed ACO_R or CGA algorithms (Figure 1c). In this step, the algorithm tries to propose optimum values for variance and average air temperature, making sure that the difference between the predicted and actual values is minimal. In Figure 1d, the ANFIS predicts the air temperature using the proposed averages and variances. The proposed averages and variances are used to predict air temperature in the training, validation and test stages. The performance of the proposed model improves if the difference between the target temperature (observed) and the model temperature (prediction) is small. The best maximum iteration, initial population, *per* cent of crossover and mutation in the CGA algorithm respectively were 500, 80, 0.8 and 0.2, respectively; and the best maximum iteration, population size, ratio fitness, conversion ratio fitness to pheromones (Q), power factor of phenomena (Alpha) and heuristic (Beta) and evaporation of phenomena (Roh) in the ACO_R were 250, 60, 15, 2.1, 1 and 0.02, respectively.

2.2.2 | Deferential evolution (DE) and particle swarm optimization (PSO)

The DE and PSO algorithms have acceptable performance for continuous problems. Consequently, they have better performance in solving environmental and hydrological problems. Moreover, the DE and PSO have a high convergence speed, simple structure, are independent from the application and easy to implement. They use a global search method and can solve complex problems. These features make them a suitable alternative to train and optimize the ANFIS system (Hasanipanah *et al*., 2016).

The difference between the ANFIS-PSO/ANFIS-DE methods and the ANFIS-GA and ANFIS-ACO_R is their optimization technique. As shown in Figure 2, input and output data are loaded and a fuzzy system is generated. The system is then optimized by the suggested algorithm and the best variances and averages are calculated. Lastly, the air temperature was modelled, and the results were reported at three parts: training, validation and test.

The best maximum iteration, population size, inertia weight, inertia weight reduction factor, personal and global best learning co-efficient in the ANFIS-PSO were 800, 90, 1.15, 0.90, 2 and 2.15, respectively; and the best population size, maximum iteration, *per* cent of crossover, lower and upper bound of beta in the ANFIS-DE were 50, 800, 0.4, 0.2 and 0.9, respectively.

2.3 | Performance evaluation

Three statistical scores, namely, the co-efficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and Nash–Sutcliffe efficiency (NSE), were used to evaluate model performance:

$$R^2 = \left[\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y}) \Big/ \sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2}\,\right]^2 \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-y_i)^2} \tag{2}$$

$$\mathrm{MAE} = \sum_{i=1}^{n}\left(\frac{|x_i-y_i|}{n}\right) \tag{3}$$

$$\mathrm{NSE} = \left[1-\frac{\sum_{i=1}^{n}(x_i-y_i)^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2}\right] \tag{4}$$

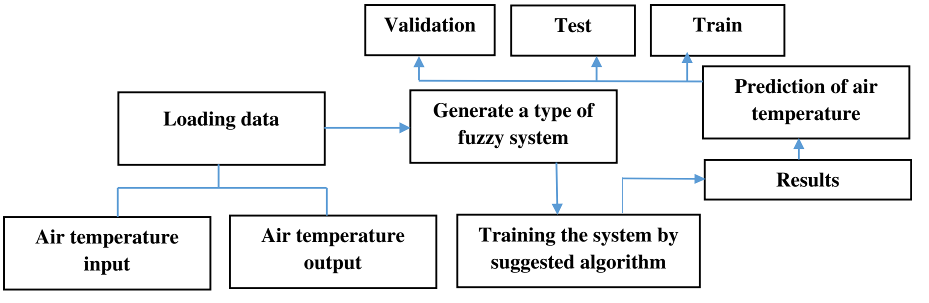

FIGURE 1 Steps of the suggested models

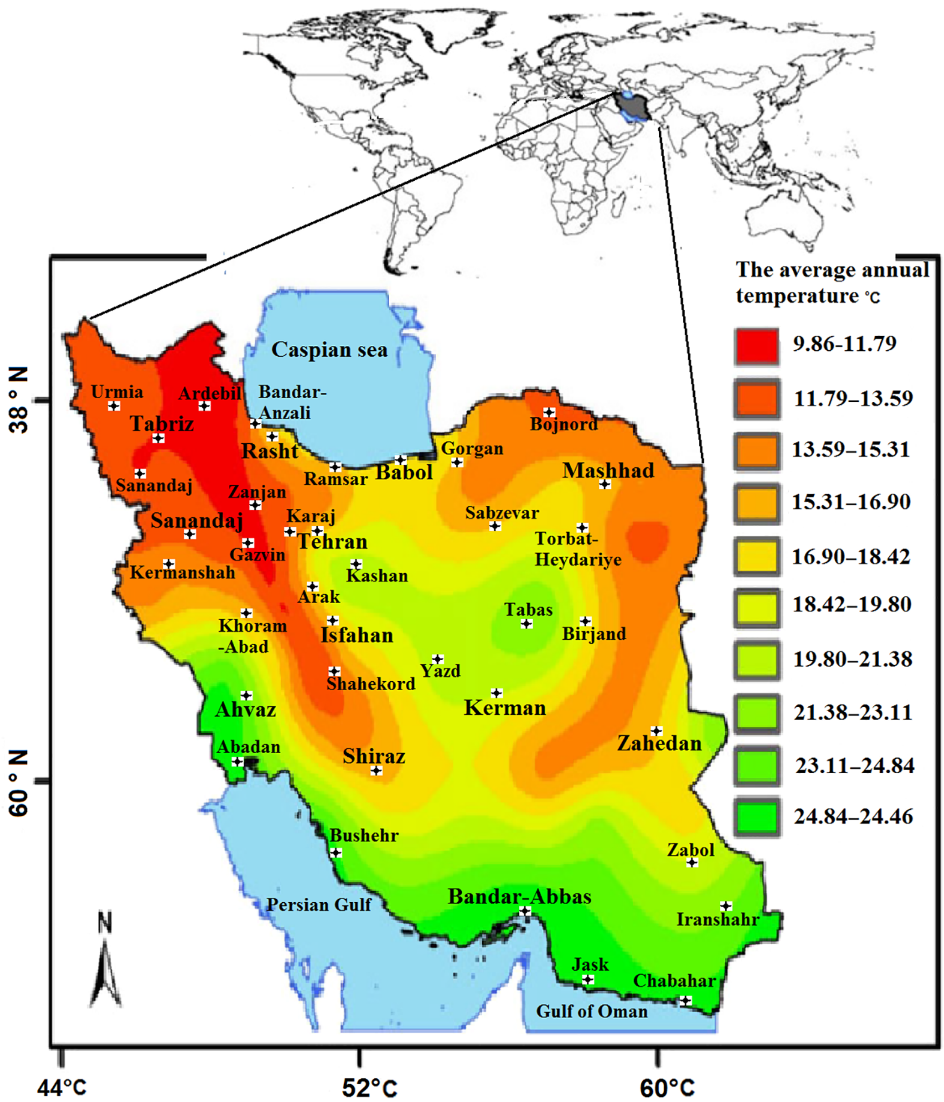

FIGURE 2 Case study area

where x_i and $\bar{x}$ represent the observed values and their mean; and y_i and $\bar{y}$ represent the predicted values and their mean, respectively.

2.4 | Case study

Iran, with an area about 1,648,000 km^2, is located in the southwest of Asia (Middle East) and lies approximately at 25–40 ° N, 44–64 ° E (Figure 2). Its most important mountains are the Alborz and Zagros ranges, which stretch from northwest to northeast and from northwest to southeast, respectively. These ranges play an important role in the non-uniform spatial and temporal distribution of precipitation in the whole country. Climatic indices and geographical conditions of some meteorological stations of Iran are presented in Table 1 and Figure 2. Most cities in Iran, such as Tehran, Isfahan, Shiraz and Mashhad, have a mountain climate. Other regions, such as Kerman and Zahedan, have arid to semi-arid climates. In these regions, the maximum temperature is > 40°C in summer and the minimum is < −5°C in winter. Precipitation is < 100 mm in most areas. The climate of humid subtropical regions, such as Babol and Rasht, located in the northern part of the Alborz mountain range, has an average annual precipitation of > 1,000 mm and the temperature fluctuates around between about 30 and 5°C in summer and winter, respectively. The climatic condition of the west and northwest regions of the Zagros mountain range changes to cold and low humidity at weather stations such as Tabriz and Sanandaj. These regions usually have cold winters with a minimum average temperature of about −10 to −15°C. In some areas to the south of Iran, air temperature and humidity increase to 55°C and 90%, respectively.

2.5 | Methodology

The monthly temperature of six stations (Isfahan, Shiraz, Kerman, Bandar-Abbas, Sanandaj and Babol) with different climate indices were selected as input parameters for the

TABLE 1 Geographical and temperature information of study area

No.	Station	Longitude		Latitude		Altitude	°C[a]	°C[b]	°C[c]	No.	Station	Longitude		Latitude		Altitude	°C[a]	°C[b]	°C[c]
1	Bushehr	50	49	28	58	9	15.9	23.0	35.5	21	Chabahar	60	37	25	17	8	19.1	26.1	32.8
2	Tabriz	46	17	38	5	1,361	−0.1	9.9	23.0	22	Iranshahr	60	42	27	12	591	14.4	27.1	38.3
3	Isfahan	51	40	32	37	1,550	4.5	17.3	28.7	23	Abadan	48	15	30	22	6.6	13.5	26.0	38.5
4	Birjand	59	12	32	52	1,491	0.9	16.4	30.2	24	Torbat-Heydariye	59	16	35	13	1,450	0.6	14.1	26.7
5	Mashhad	59	38	36	16	999	2.4	15.1	29.7	25	Sabzevar	57	39	36	12	972	5.5	17.7	31.2
6	Bojnord	57	16	37	28	1,112	0.3	12.9	27.6	26	Kashan	51	27	33	59	982	6.84	19.4	31.8
7	Ahvaz	48	40	31	20	22.5	14.9	26.0	40.7	27	Khoy	44	58	38	33	1,103	−0.2	12.5	25.6
8	Shahrekord	50	51	32	17	2,048	−3.5	11.5	24.7	28	Babol	52	39	36	43	−21	9.5	17.3	27.1
9	Zahedan	60	53	29	28	1,370	−3.5	19.1	32.4	29	Ramsar	50	40	36	54	−20	8.9	16.3	25.6
10	Shiraz	52	36	29	32	1,484	6.1	17.7	30.3	30	Bandar-Anzali	49	27	37	29	−23	9.7	16.4	25.7
11	Qazvin	50	3	36	15	1,279	1.0	13.7	27.3	31	Tabas	56	55	33	36	711	10.7	22.6	34.8
12	Sanandaj	47	0	36	20	1,373	−0.5	12.8	25.6	32	Jask	57	46	25	38	5.2	21.3	27.4	33.9
13	Kerman	56	58	30	15	1,753	1.3	16.8	30.2	33	Bandar-Lenge	54	50	26	32	22	19.3	27.8	33.9
14	Kermanshah	47	9	34	21	1,318	0.7	15.3	28.9	34	Bam	58	21	29	6	1,066	12.0	23.5	35.6
15	Gorgan	54	24	36	54	0	7.0	17.3	31.5	35	Saqqez	46	21	36	15	1,522	−4.5	11.3	25.1
16	Rasht	49	37	37	19	−8.6	7.5	15.9	29.0	36	Zabol	61	29	31	2	489	8.8	22.5	36.3
17	Khoram-Abad	48	17	33	26	1,147	3.2	16.6	30.0	37	Urmia	45	3	37	40	1,328	−0.2	11.3	23.9
18	Arak	49	55	34	6	1,708	1.12	13.8	26.6	38	Karaj	50	54	35	55	1,312	2.6	15.7	27.0
19	Bandar-Abas	56	22	27	13	9.8	17.5	24.8	36.7	39	Ardebil	48	17	38	15	1,332	−5.3	8.9	24.1
20	Yazd	54	17	31	54	1,237	7.1	19.8	32.8	40	Zanjan	48	29	36	41	1,663	−2.9	10.8	24.3

Notes: [a]Average of annual minimum temperature.
[b]Average of annual mean temperature.
[c]Average of annual maximum temperature.

models used in the present study. The authors tried to predict the temperature of the most important stations of Iran (Mashhad, Zahedan, Ahvaz, Rasht and Tabriz). This process used the ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO models to predict Iran's climate. Note that among the selected stations as input and output parameters, Isfahan and Mashhad have a foothills climate, Kerman and Zahedan have an arid climate, Ahvaz has a hot and humid climate, Sanandaj and Tabriz have a cold climate in the winter, and Rasht and Babol have a humid subtropical climate. The data were collected from the meteorological organization of Iran (http://www.weather.ir). Monthly air temperatures of the six above mentioned stations from 1951 to 2014 were used as system input and outputs.

3 | RESULTS AND DISCUSSION

3.1 | Prediction of air temperatures of foothills regions

3.1.1 | Mashhad

The ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO models improved the classic ANFIS in the study area. In fact, for minimum temperatures the RMSE–NSE (1.69–0.72) of the classic ANFIS in the validation stage was decreased (increased) to 1.25 (0.93), 1.27 (0.94), 1.21 (0.93) and 1.22 (0.93) using the ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO models, respectively. This trend continued for other temperature indices, as shown in Table 2. The performance of the ANFIS-PSO for average temperature was better than for minimum temperature, and ranked first because it had lower RMSE and MAE, and higher R^2 compared with the ANFIS-GA. The ANFIS-GA performed better in the prediction of sudden changes of average temperature, while the ANFIS-PSO performed better in the prediction of average changes. Moreover, the ANFIS had the lowest accuracy in the prediction of extreme and average temperatures with highest RMSE and MAE and consequently scored the weakest model. Note that combined models (ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO) in Mashhad showed the worst performance in the prediction of average (or mean) temperature.

Hybrid models of the ANFIS exhibited better performance in predicting maximum temperature. The ANFIS-GA, in close competition with the ANFIS-DE, was selected as the best model with lower RMSE and MAE and higher R^2. Kachitvichyanukul (2012) showed that the GA in the optimization of continuous and non-continuous data performs better and the present results confirm this. In fact, the ANFIS-GA exhibited the best accuracy for the prediction of most temperature indices in the study areas. The present

TABLE 2 Prediction of the minimum, mean and maximum temperatures of Mashhad City

	R^2			Root mean square error (RMSE)			Mean absolute error (MAE)			Nash–Sutcliffe efficiency (NSE)		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
Minimum												
ANFIS	0.98	0.91	0.72	0.90	1.31	1.69	1.01	2.29	2.99	0.98	0.90	0.72
ANFIS-ACO$_R$	0.96	0.95	0.93	1.27	1.23	1.25	1.93	1.8	1.85	0.92	0.95	0.93
ANFIS-GA	0.94	0.92	0.93	1.17	1.3	1.27	1.66	2.06	2.02	0.94	0.93	0.94
ANFIS-DE	0.93	0.93	0.93	1.26	1.26	1.21	1.9	1.91	1.85	0.93	0.93	0.93
ANFIS-PSO	0.95	0.91	0.93	1.03	1.38	1.22	1.36	2.26	2.08	0.95	0.91	0.93
Mean												
ANFIS	0.95	0.79	0.55	1.11	1.57	1.44	8.34	2.99	2.97	0.95	0.82	0.66
ANFIS-ACO$_R$	0.91	0.91	0.88	1.33	1.41	1.44	2.11	2.26	2.36	0.91	0.92	0.89
ANFIS-GA	0.91	0.91	0.92	1.32	1.36	1.36	2.07	2.23	2.14	0.91	0.92	0.92
ANFIS-DE	0.91	0.91	0.90	1.35	1.42	1.35	2.16	2.26	2.23	0.91	0.91	0.90
ANFIS-PSO	0.93	0.91	0.91	1.22	1.33	1.29	1.80	2.10	2.09	0.93	0.92	0.92
Maximum												
ANFIS	0.98	0.74	0.88	0.77	1.61	1.22	0.75	3.00	2.49	0.99	0.97	0.98
ANFIS-ACO$_R$	0.94	0.91	0.95	1.17	1.21	1.14	1.62	1.67	1.63	0.99	0.99	0.99
ANFIS-GA	0.95	0.94	0.93	1.15	1.16	1.12	1.55	1.56	1.55	0.99	0.99	0.99
ANFIS-DE	0.94	0.94	0.94	1.13	1.17	1.23	1.54	1.63	1.66	0.99	0.99	0.99
ANFIS-PSO	0.96	0.93	0.90	1.00	1.20	1.26	1.22	1.85	1.88	0.99	0.99	0.99

study used continuous GA for training the ANFIS. The ANFIS without the GA training ranked last (Table 2).

3.1.2 | Prediction of air temperatures in an arid climate (Zahedan)

Table 3 shows that the ANFIS has weak performance in modelling minimum temperature at this station compared with the ANFIS-GA. In fact, R^2 and NSE in the validation and test stages are lower for the ANFIS compared with the ANFIS-GA. The ANFIS-ACO$_R$ and ANFIS-DE were selected as the best because of the better MAE (Table 3). The performance of the models in this climate zone showed that a global search for optimal points is an advantage with respect to a local search. For all the models that used a global search technique, the R^2 was high.

At this location, the hybrid models had good performance when predicting the average temperature. The ANFIS-PSO and ANFIS-ACO$_R$ were ranked first. The ANFIS was the worst model. The heuristic global optimization methods, such as the GA, ACO or PSO, had much better convergence properties than nonlinear least squares methods and do not rely on a "good" starting estimate of the model parameters to locate the global minimum. In the case of predicting the average temperature, the RMSE = 0.98 and NSE = 0.98 of the classic ANFIS in the validation stage decreased (increased) to 0.84 (0.99), 0.90 (0.99) and 0.88 (0.99) using the ANFIS-ACO$_R$, ANFIS-GA and ANFIS-PSO models, respectively.

3.1.3 | Prediction of air temperatures in a hot and humid climate (Ahvaz)

At this location, the ANFIS-GA and ANFIS-DE were the best models, while the classic ANFIS ranked last (Table 4). Compared with other areas (Tables 3, 5 and 6) the performance of the ANFIS was better probably linked to the low-temperature variability in Ahvaz. In the validation stage, the RMSE–NSE (1.27–0.95) of the classic ANFIS in predicting the minimum temperature decreased (increased) to 1.09 (0.98), 0.97 (0.98), 1.05 (0.98) and 0.94 (0.98) using the ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO models, respectively. A similar trend can also be observed for the prediction of average (mean) and maximum temperatures.

3.1.4 | Prediction of air temperatures in a humid subtropical climate (Rasht)

The performance of the proposed models for the prediction of climatic indices was completely different in the humid subtropical climatic condition. The proposed models provided the

TABLE 3 Prediction of the minimum, mean and maximum temperatures of Zahedan City

	R^2			Root mean square error (RMSE)			Mean absolute error (MAE)			Nash–Sutcliffe efficiency (NSE)		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
Minimum												
ANFIS	0.98	0.63	0.80	0.91	1.57	1.31	1.03	3.81	3.02	0.91	0.70	0.83
ANFIS-ACO$_R$	0.90	0.84	0.94	1.26	1.47	1.22	1.97	2.85	2.23	0.93	0.90	0.94
ANFIS-GA	0.90	0.94	0.90	1.92	1.14	1.39	1.21	1.75	2.06	0.94	0.95	0.93
ANFIS-DE	0.90	0.87	0.93	1.29	1.43	1.26	2.11	2.45	2.15	0.93	0.90	0.94
ANFIS-PSO	0.93	0.87	0.85	1.06	1.45	1.35	1.54	2.63	2.39	0.95	0.90	0.90
Mean												
ANFIS	0.99	0.97	0.93	0.65	0.98	0.98	0.54	1.15	1.19	0.99	0.99	0.98
ANFIS-ACO$_R$	0.97	0.97	0.98	0.95	0.94	0.84	1.06	1.1	0.96	0.96	0.99	0.99
ANFIS-GA	0.97	0.96	0.97	0.89	0.99	0.90	0.94	1.12	1.07	0.99	0.99	0.99
ANFIS-DE	0.97	0.97	0.96	0.91	0.93	0.97	0.98	0.97	1.05	0.99	0.99	0.99
ANFIS-PSO	0.98	0.97	0.97	0.78	0.91	0.88	0.73	0.99	0.95	0.99	0.99	0.99
Maximum												
ANFIS	0.99	0.80	0.78	0.62	1.3	1.26	0.49	2.34	2.31	0.99	0.98	0.97
ANFIS-ACO$_R$	0.96	0.95	0.96	0.94	0.97	0.93	1.06	1.2	1.12	0.99	0.99	0.99
ANFIS-GA	0.96	0.95	0.95	0.92	0.96	1.01	0.99	1.07	1.15	0.99	0.99	0.99
ANFIS-DE	0.96	0.96	0.95	0.92	0.94	1.01	1.02	1.08	1.15	0.99	0.99	0.99
ANFIS-PSO	0.96	0.96	0.97	0.9	0.93	0.92	0.97	1.01	1.04	0.99	0.99	0.99

TABLE 4 Prediction of the minimum, mean and maximum temperatures of Ahvaz City

	R^2			Root mean square error (RMSE)			Mean absolute error (MAE)			Nash–Sutcliffe efficiency (NSE)		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
Minimum												
ANFIS	0.99	0.90	0.91	0.58	1.16	1.27	0.43	1.79	1.82	0.99	0.92	0.95
ANFIS-ACO$_R$	0.97	0.96	0.96	0.96	1.03	1.09	1.12	1.23	1.32	0.99	0.98	0.98
ANFIS-GA	0.97	0.95	0.97	0.86	1.02	0.97	0.93	1.22	1.15	0.98	0.97	0.98
ANFIS-DE	0.96	0.97	0.96	1.01	1.02	1.05	1.21	1.2	1.25	0.98	0.99	0.98
ANFIS-PSO	0.98	0.91	0.97	0.82	1.08	0.94	0.8	1.55	1.31	0.99	0.97	0.98
Mean												
ANFIS	0.99	0.98	0.98	0.47	0.72	0.75	0.27	0.7	0.70	0.99	0.98	0.97
ANFIS-ACO$_R$	0.99	0.99	0.99	0.73	0.82	0.84	0.62	0.77	0.73	0.99	0.99	0.99
ANFIS-GA	0.99	0.99	0.99	0.71	0.66	0.69	0.59	0.54	0.56	0.99	0.99	0.99
ANFIS-DE	0.99	0.99	0.99	0.74	0.72	0.76	0.64	0.66	0.66	0.99	0.99	0.99
ANFIS-PSO	0.99	0.99	0.99	0.62	0.65	0.69	0.45	0.52	0.54	0.99	0.99	0.99
Maximum												
ANFIS	0.99	0.96	0.93	0.64	1.06	1.20	0.51	1.46	1.61	0.99	0.94	0.95
ANFIS-ACO$_R$	0.98	0.97	0.97	0.96	1.01	0.96	1.09	1.22	1.18	0.99	0.99	0.99
ANFIS-GA	0.98	0.97	0.97	0.93	0.97	0.98	1.04	1.08	1.14	0.99	0.99	0.99
ANFIS-DE	0.97	0.97	0.98	0.95	1.01	1.00	1.08	1.15	1.16	0.99	0.99	0.99
ANFIS-PSO	0.98	0.96	0.96	0.81	1.06	1.02	0.82	1.37	1.33	0.99	0.99	0.99

weakest results for the prediction of average temperature. In other words, all the models showed similar and close results for average temperature (Table 5). However, the improvement of the classic ANFIS model is the highest in the prediction of maximum temperatures. In the validation stage, the ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO models decreased (increased) the RMSE (NSE) of the classic ANFIS in predicting the maximum temperature to 1.26 (0.99), 1.24 (0.99), 1.17 (0.99) and 1.29 (0.99), respectively. Also, the ANFIS-DE had the most accurate predictions of minimum and maximum temperatures of this climatic zone. In this climate zone, the correlation co-efficient (R) between inputs of max air temperature was less than those of the other climate zones, so the ANFIS algorithms could not optimize the system as they were either trapped in local optima or overfitting phenomena. The suggested models (ANFIS-ACO$_R$, ANFIS-GA, ANFIS-DE and ANFIS-PSO) have the ability to avoid being trapped in local optima or overfitting phenomena. Therefore, they have the best performance in solving nonlinear problems.

3.1.5 | Prediction of air temperatures in a cold climate (Tabriz)

Table 6 shows that the hybrid models predicted average, minimum and maximum temperature in the region with a cold climate satisfactorily compared with the classic ANFIS approach. The performance of the ANFIS-GA, ANFIS-DE and ANFIS-ACO$_R$ for the prediction of minimum temperature was in close agreement. The ANFIS-PSO ranked second and the ANFIS ranked last with the weakest performance. The PSO's weaker performance was linked to the high volume of computations when predicting the minimum temperature, which involved six nonlinear inputs to predict the cold winter temperature in Tabriz.

The average temperature prediction showed close agreement among the models. In fact, modelling average temperature is easier than the minimum and maximum because, when using average data as the input, extremum points are reduced. As a result, modelling is much easier to perform. Therefore, all models, more and less powerful ones, had a good ability to predict average air temperature. On the other hand, when predicting the minimum and maximum temperatures, models face an extremum point that should be modelled and predicted. Thus, the more powerful is the model, the better the results observed.

3.2 | Summary of the models' performance

The ANFIS-ACO$_R$, ANFIS-GA, ANFIS-PSO and ANFIS-DE significantly improve the performance of the classic ANFIS when predicting minimum, average and maximum

TABLE 5 Prediction of the minimum, mean and maximum temperatures of Rasht City

	R^2			Root mean square error (RMSE)			Mean absolute error (MAE)			Nash–Sutcliffe efficiency (NSE)		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
Minimum												
ANFIS	0.99	0.72	0.91	0.64	1.24	1.19	0.5	2.44	2.10	0.99	0.80	0.95
ANFIS-ACO_R	0.96	0.98	0.96	0.92	0.86	1.03	1.03	0.92	1.06	0.97	0.97	0.98
ANFIS-GA	0.97	0.95	0.97	0.86	1.02	0.97	0.93	1.22	1.15	0.98	0.97	0.98
ANFIS-DE	0.96	0.97	0.97	0.95	0.87	0.92	1.10	0.96	0.98	0.97	0.97	0.98
ANFIS-PSO	0.98	0.93	0.95	0.73	1.05	1.04	0.66	1.39	1.39	0.98	0.95	0.96
Mean												
ANFIS	0.99	0.98	0.98	0.43	0.61	0.58	0.99	0.6	0.60	0.99	0.98	0.97
ANFIS-ACO_R	0.99	0.99	0.99	0.71	0.66	0.64	0.46	0.49	0.46	0.99	0.99	0.99
ANFIS-GA	0.99	0.99	0.99	0.73	0.58	0.6	0.42	0.48	0.45	0.99	0.99	0.99
ANFIS-DE	0.99	0.99	0.99	0.43	0.61	0.58	0.45	0.47	0.46	0.99	0.99	0.99
ANFIS-PSO	0.99	0.99	0.99	0.71	0.66	0.64	0.34	0.48	0.47	0.99	0.99	0.99
Maximum												
ANFIS	0.95	0.21	0.17	0.84	1.62	1.76	0.90	3.87	4.02	0.99	0.92	0.93
ANFIS-ACO_R	0.81	0.82	0.82	1.18	1.33	1.26	1.73	2.07	1.98	0.99	0.99	0.99
ANFIS-GA	0.86	0.74	0.79	1.59	1.3	1.24	1.59	2.13	2.00	0.99	0.99	0.99
ANFIS-DE	0.8	0.84	0.85	1.21	1.29	1.17	1.79	2.02	1.84	0.99	0.99	0.99
ANFIS-PSO	0.88	0.86	0.68	1.07	1.15	1.29	1.41	1.69	1.83	0.99	0.99	0.99

TABLE 6 Prediction of the minimum, mean and maximum temperatures of Tabriz City

	R^2			Root mean square error (RMSE)			Mean absolute error (MAE)			Nash–Sutcliffe efficiency (NSE)		
	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation	Train	Test	Validation
Minimum												
ANFIS	0.99	0.84	0.91	0.8	1.48	1.36	0.77	2.84	2.46	0.99	0.85	0.89
ANFIS-ACO_R	0.96	0.94	0.95	1.12	1.17	1.15	1.53	1.64	1.65	0.96	0.95	0.95
ANFIS-GA	0.96	0.94	0.96	1.12	1.17	1.08	1.5	1.81	1.61	0.96	0.95	0.96
ANFIS-DE	0.95	0.95	0.97	1.16	1.18	1.07	1.66	1.64	1.49	0.95	0.96	0.97
ANFIS-PSO	0.97	0.96	0.91	0.99	1.18	1.32	1.23	1.55	1.85	0.97	0.96	0.89
Mean												
ANFIS	0.99	0.97	0.97	0.51	0.79	0.88	0.34	0.98	0.95	0.99	0.97	0.97
ANFIS-ACO_R	0.99	0.98	0.99	0.81	0.75	0.77	0.77	0.82	0.75	0.99	0.99	0.99
ANFIS-GA	0.99	0.99	0.98	0.74	0.82	0.83	0.64	0.82	0.82	0.99	0.99	0.99
ANFIS-DE	0.99	0.98	0.99	0.77	0.83	0.76	0.7	0.85	0.78	0.99	0.99	0.99
ANFIS-PSO	0.99	0.98	0.99	0.69	0.74	0.80	0.57	0.8	0.77	0.99	0.99	0.99
Maximum												
ANFIS	0.99	0.89	0.94	0.67	1.36	1.21	0.57	2.33	2.07	0.99	0.93	0.96
ANFIS-ACO_R	0.97	0.98	0.98	0.96	0.96	0.98	1.11	1.14	1.13	0.99	0.99	0.99
ANFIS-GA	0.97	0.97	0.98	0.97	0.93	0.95	1.13	1.06	1.08	0.99	0.99	0.99
ANFIS-DE	0.97	0.98	0.97	0.98	0.9	0.96	1.14	0.96	1.04	0.99	0.99	0.99
ANFIS-PSO	0.98	0.95	0.97	0.79	1.11	1.00	0.76	1.54	1.39	0.99	0.99	0.99

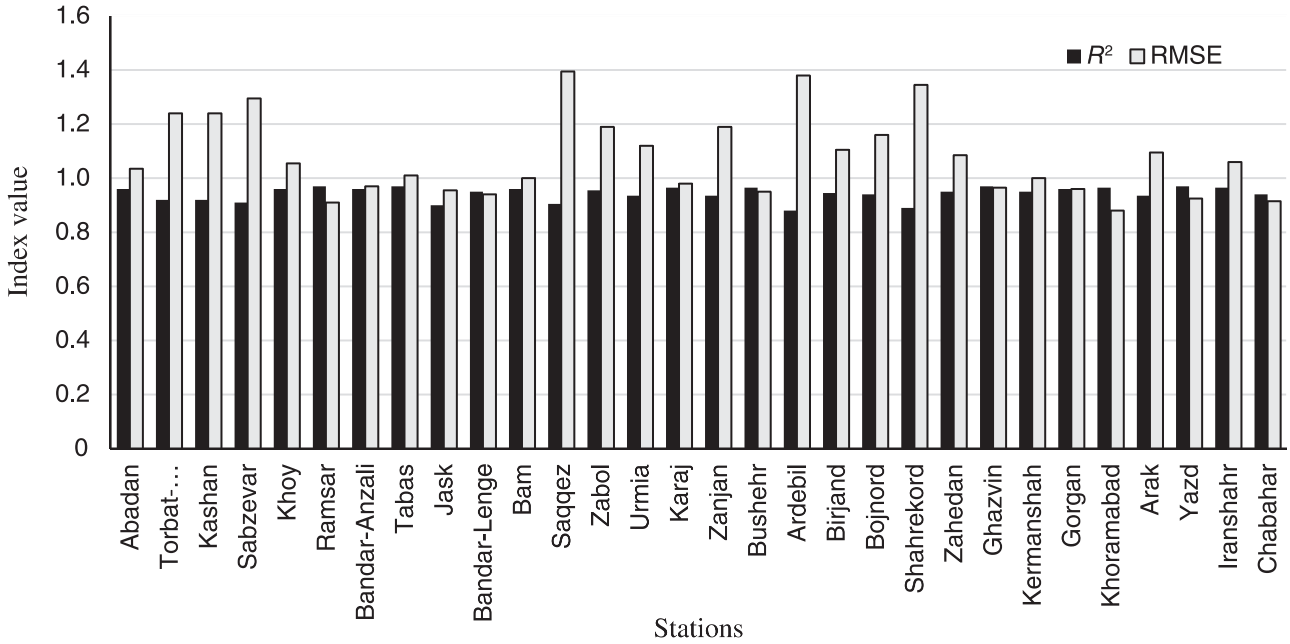

FIGURE 3 Prediction of the minimum temperature of different weather stations of Iran by adaptive neuro-fuzzy inference system (ANFIS) with a genetic algorithm (GA)

temperatures in Iran. While the ANFIS-GA was not the best model at some locations in Iran, it was the most stable model among those used in the present study. The ANFIS-DE ranked second. The ANFIS-PSO had the best performance in some locations and ranked third.

The reliable performance of the ANFIS-GA is due to: (1) the appropriate ability of the GA to use a global search method; (2) to be independent of specific applications—it means that there is no difference what issue GA is selected to solve because it can optimize it without considering the nature of the problem; (3) the ability to solve complex problems and be optimizable (e.g. some stations may have a high correlation between inputs and output); and (4) using a continuous function for a continuous problem.

The ANFIS-GA was not the best at some stations because of a low correlation co-efficient. In these cases, the ACO_R and DE-based trained systems are better than the GA, because these algorithms reach convergence despite the complex problems.

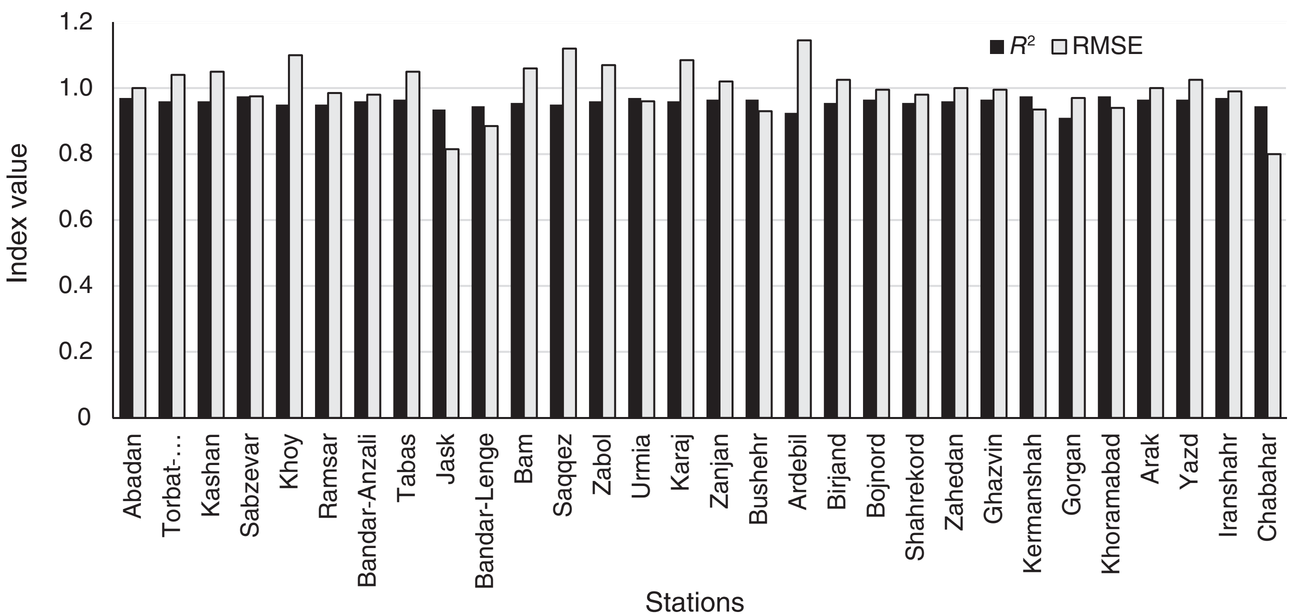

FIGURE 4 Prediction of average temperature of different weather stations of Iran by adaptive neuro-fuzzy inference system (ANFIS) with a genetic algorithm (GA)

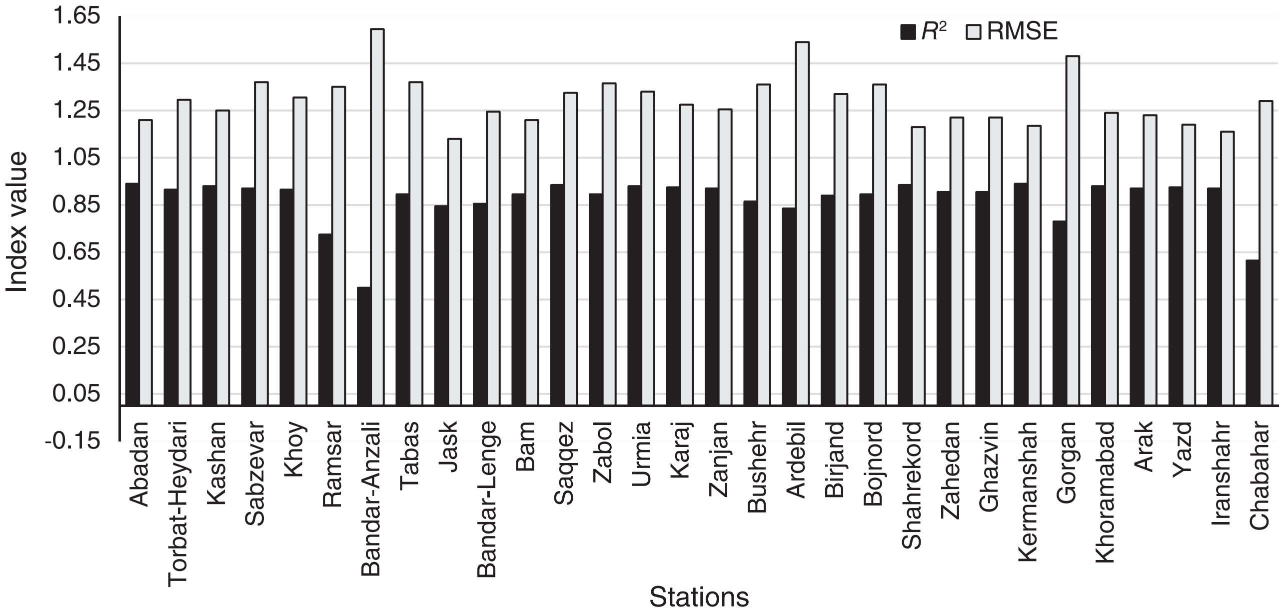

FIGURE 5 Prediction of maximum temperature of different weather stations of Iran by adaptive neuro-fuzzy inference system (ANFIS) with a genetic algorithm (GA)

The time required for optimization is an important element for the selection of the best model. Results indicate that the DE and PSO are the fastest algorithms when solving problems, and on average 1,000 iterations took about 120 s. The GA ranked second with an optimization reached after 140 s. The ACO_R ranked last with a relatively low speed (about 360 s). Note that the speed is directly linked to the complexity of the problem: the more complex the problem, the slow the convergence.

3.3 | Validation of the presented method

Extreme and average temperatures of 29 weather stations with different climatic features were predicted using the ANFIS-GA model (Figures 3–5). Note that during the training, test and validation stages, this model was similar to the ANFIS-DE. This is probably due to the suitability and consistency of the DE algorithm's performance when modelling a wide range of air temperatures in different regions with different climatic conditions. The results of the training stage are not presented here as they are deemed out of scope.

4 | CONCLUSIONS

Forecasting of the minimum, average and maximum air temperatures is important for the management of water resources and water supplies in Iran. The results of a variety of algorithms showed that, in most cases, all suggested methods improved the classic adaptive neuro-fuzzy inference system (ANFIS) when modelling the minimum, average and maximum temperatures at stations in Iran with different climatic conditions. Among the suggested algorithms, the genetic algorithm (GA) had the best performance for maximum temperature prediction, but it did not perform so well when forecasting average temperature. In the validation stage, the root mean square error–Nash–Sutcliffe efficiency (RMSE/NSE) of the classic ANFIS model in maximum temperature prediction decreased (increased) from 1.22 (0.98) to 1.12 (0.99)°C for Mashhad, from 1.26 (0.97) to 1.01 (0.99)°C for Zahedan, from 1.20 (0.95) to 0.98 (0.99)°C for Ahvaz, from 1.76 (0.93) to 1.24 (0.99)°C for Rasht, and from 1.21 (0.96) to 0.95 (0.99)°C for Tabriz. The overall evaluation suggests that the accuracy rank (from best to worst) of the used models is ANFIS-GA, ANFIS-DE, ANFIS-PSO and ANFIS-ACO_R in the prediction of monthly air temperatures of Iran.

ACKNOWLEDGEMENTS

The authors thank the Iran Meteorological Organization (http://www.weather.ir) for providing the necessary data in order to carry out this investigation.

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How to cite this article: Azad A, Kashi H, Farzin S, *et al.* Novel approaches for air temperature prediction: A comparison of four hybrid evolutionary fuzzy models. *Meteorol Appl.* 2020;27:e1817. https://doi.org/10.1002/met.1817